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Benefit Incidence and the Timing of Program Capture

Peter Lanjouw
Martin Ravallion

Benefits from schooling and antipoverty programs in rural India were captured early by the nonpoor. The poor tend to benefit from program expansion, and lose from contraction. Conventional methods of assessing benefit incidence hide this fact.

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Summary findings

Survey-based estimates of average program participation conditional on income are often used in assessing the distributional impacts of public spending reforms.

But program participation could well be nonhomogeneous, so that marginal impacts of program expansion or contraction differ greatly from average impacts.

Using the geographic variation found in sample survey data for rural India for 1993–94, Lanjouw and Ravallion estimate the marginal odds of participating in schooling and antipoverty programs. Their results suggest early capture of these programs by the nonpoor.

Thus, conventional methods of assessing benefit incidence underestimate the gains to India's rural poor from higher public outlays, and their loss from program cuts.

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Benefit Incidence and the Timing of Program Capture

Peter Lanjouw and Martin Ravallion[1]

World Bank

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1. Introduction

"Benefit incidence analysis" (BIA) is widely used to infer the distributional impacts of public spending. The key data input to traditional BIA is a survey-based estimate of how the odds of participation in various public programs vary with the welfare indicator. Typically, the average participation rates for a specific public program are tabulated against household income or expenditure per person. A subsidy rate for each category of spending is then applied to the participation numbers to infer the incidence of the gains from public spending and from reallocations between categories of spending.[2]

While BIA is a well established tool in understanding who benefits from public spending, the method is known to have its limitations.[3] One concern is that the subsidy per unit of usage may be a poor indicator of "benefit"; unlike the commodities obtained on markets, utilization of a publicly supplied good is unlikely, as a general rule, to reveal the value (specifically the marginal rates of substitution with private goods) that consumers attach to that good.

Another concern is that average benefits (even when correctly measured) need not be a reliable guide to the incidence of a change in aggregate spending on a given program, or the distributional impact of a reallocation of the budget between programs. Consider first the case of a pure public good i.e., a good for which one person's consumption does not deplete the amount left for anyone else. For such a good, the quantity constraints on consumption entail that marginal rates of substitution could vary greatly between consumers at the current level of public

2 Examples of this type of analysis include Meerman (1979), Selowsky (1979), Meesook (1984), Medel et al., (1992), van de Walle (1995), and Demery (1997).

3 For overviews of the conceptual and practical issues that arise in using this method to assess how much the poor gain from public spending see Selden and Wasylenko (1992) and van de Walle (1998).

provisioning. A small reduction in supply could then have a very different value to different consumers. This will be less likely with a large change in supply of the public good for then the infra-marginal losses of consumer surplus will dominate (Piggott and Whalley, 1987).

What about the (arguably) more common case of publicly-supplied private goods, including transfers? These are typically also subject to quantity constraints. However, unlike public goods, there is a program allocation across consumers which also comes into play. The current distributional impacts of a change in provisioning will depend on how well positioned different socio-economic groups are to gain from marginal expansions, given the history of past allocations under the public program. Suppose that the non-poor were able to capture the bulk of the gain when the program was first introduced, but are now virtually satiated at the margin. Then the poor will gain a large share of the marginal benefits from program expansion even though their share of average benefits is low. Similarly, finding that the non-poor obtained a high share of average benefits could be perfectly consistent with the poor bearing the bulk of the cost of a contraction in aggregate outlays.[4] We know surprisingly little about how much difference this might make to the inferences which are routinely drawn about the incidence of changes in public spending from standard incidence calculations.[5] The timing of program capture by different income groups could well be critical to the policy conclusions drawn about the incidence of gains and losses from public spending reforms.

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4 For example, see the results of Bidani and Ravallion (1996), who compare the impacts of cross-country differences in public health spending on health indicators for the poor versus the non-poor, and find that differences in public health spending matter far more to the health outcomes of the poor than the non-poor.

5 Piggott and Whalley (1987) use simulations to demonstrate that marginal versus average incidence for a public good can differ substantially. Studies which have tracked changes in incidence over time have also thrown light on how the composition of beneficiaries changes over time; for further discussion see Lipton and Ravallion (1995, section 6.4.3) and for examples see Hammer et al., (1995) and van de Walle (1995).

We examine this issue empirically, using new data on participation in primary schooling and the main anti-poverty programs in rural India, based on a large national survey for 1993-94. We provide estimates of the average participation rates, following reasonably standard methods. We then address the above concern about these methods by estimating marginal participation rates, and we compare the average and marginal odds of participation. To estimate the marginal odds of participation, we exploit the fact that there are large geographic differences across India in the scale of each of the various types of public programs. By comparing average participation rates of a given income stratum across areas with different levels of average participation we can identify the scale effect on the socio-economic composition of participants.

The following section discusses in general terms the distinction between average and marginal incidence, and why they might differ. For this purpose we use a simple theoretical model of the political-economy of targeting. The two sections which follow then describe our methods and data respectively. This is followed by a discussion of the results for both primary education and the anti-poverty programs. Section 6 concludes.

2. How does the composition of program participation vary with scale?

Let the population be divided into two or more groups according to income (or some other criterion). For each income group we measure the participation rate in a public program, and we examine the effect of expanding the overall size of the program. If the group-specific participation rates stay the same then we shall say that the composition of program participation is homogeneous.[6] If 40% of participants are poor when 100 participants are covered then 40%

6 Strictly we mean "homogeneous of degree one".

are also poor when 1000 are covered. Policy conclusions drawn from standard benefit incidence analyses implicitly assume homogeneity. However, there is no obvious reason why this would hold.

Nonhomogeneous participation in public programs arises when the non-poor are able at certain times to capture the benefits of these programs, even when ostensibly targeted solely to the poor. This assumes that the government is either unable to target perfectly – due to information or incentive problems – or that doing so is not a political equilibrium, in that the support of the non-poor is crucial.[7] The timing of such program capture will depend on how the costs and benefits of participation vary with the scale of the program. Social programs invariably impose costs on participants, both in the form of direct cofinancing through taxes or fees, or more hidden deadweight losses from participation, such as the opportunity cost to parents of children's time at school, or costs to a non-poor person of securing participation in a means-tested program by illegal means. Such costs could well vary with the scale of the program.

For example, the geography of program placement can generate nonhomogeneous participation. Consider a country where poor areas tend to be more remote, and hence less convenient for program staff to reach. So initial placement tends to be in less poor areas. When the program is first set up, participation by the poor is more costly than when the program eventually expands into poor areas. Thus, there is <u>early capture</u> of the program by the more accessible non-poor. But after some point, marginal gains start to favor the poor through a process of public-spending "trickle down".

[7] For an overview of these issues see Besley and Kanbur (1993). For a model with the political economy of targeting in which perfect targeting is not an equilibrium see Gelbach and Pritchett (1997).

General equilibrium effects could also produce rising costs of participation in a way which differs between poor and non-poor. For example, while a small public works program may well have no effect on wages in alternative work, a large one is more likely to bid up wages and hence increase the expected foregone income of program participants. To the extent that the non-poor face better chances of getting work they will find the public employment program less and less attractive as it expands. Again, early capture by the non-poor can be expected.

These are all cases of early capture, but late capture is also possible. For example, it may be far easier for the (theoretically ineligible) non-poor to bribe officials to gain access to the program once it is more widely available and so a non-poor participant is less conspicuous.

We can formalize these arguments in a simple political-economy model of the capture of an anti-poverty by the non-poor. The model assumes that the government wants to reduce poverty with the program, but that it faces a political-economy constraint which restricts any adverse welfare impacts on the non-poor. In particular, the program imposes costs on the non-poor (such as taxes for financing the program) which depend on average participation (of the poor and non-poor). The non-poor have political influence over program placement which they use to obtain compensatory benefits. Let the cost to the non-poor be $C(X)$ where X is average participation and C is a smoothly increasing function with $C(0)=0$. Marginal cost is $C'(X)$ which could either increase or decrease with X (for C convex or concave respectively). The program is allocated between non-poor households, who each get X_n, and the poor, who get X_p. The corresponding benefits are $B(X_n)$ and $B(X_p)$ respectively, where the function B is increasing from $B(0)=0$.[8] Utility of a non-poor household is $U[Y_n + B(X_n) - C(X)]$ where Y_n is its exogenous income and the function U is strictly increasing.

Assume now that political feasibility requires that the non-poor do not lose from the program. i.e., a necessary condition for the program to continue is that:

$$U[Y_n + B(X_n) - C(X)] \geq U(Y_n) \qquad (1)$$

where $U(Y_n)$ is the fall-back utility of the non-poor without the program (X_n=X=0). Since the government values gains to the poor, the political-economy constraint will be binding in equilibrium. (For if it were not binding, then there would be a politically feasible change which benefited the poor.) Since (1) must then hold with equality, we have:

$$B(X_n) = C(X) \qquad (2)$$

Solving (2) for.

$$X_n = \Psi(X) \qquad (3)$$

tells us how program participation by the non-poor varies with average participation consistently with the political-economy constraint. The poor get the rest:

$$X_p = [X - N_n \Psi(X)]\, N_p^{-1} \qquad (4)$$

where the N_n and N_p are the proportions of the population who are non-poor and poor respectively. The marginal increment to participation by the non-poor as the program expands – the marginal participation rate of the non-poor – is given by:

$$\Psi'(X) = C'(X)\, B'(X_n)^{-1} \qquad (5)$$

8 To simplify the notation we write the B function as common between the poor and non-poor. Allowing the functions to differ makes no difference to the following analysis, though it could clearly matter to the assessment of benefit incidence in practice.

To see what this model implies for the timing of program capture, consider first the special case in which B is linear (constant marginal benefit). Then it is plain from (5) that X_n will be concave (convex) in X – implying that the marginal gains to the poor tend to rise (fall) as the program expands – whenever the program entails a decreasing (increasing) marginal cost for the non-poor. Early (late) capture will be found when the cost function is concave (convex).

With declining marginal benefit to the non-poor (B concave), a convex cost function still implies late capture. However, for early capture, the cost function must be sufficiently concave. On differentiating (5) w.r.t. X, it is readily verified that

$$\Psi''(X) = [C''(X)\, B'(X_n) - X_n'(X)\, C'(X)\, B''(X_n)]B'(X_n)^{-2} \qquad (6)$$

The necessary and sufficient condition for early capture ($\Psi''(X) < 0$) to be the only politically feasible option in this model is that that the (absolute) elasticity of marginal cost ($-XC''(X)C'(X)^{-1}$) exceeds the elasticity of participation by the non-poor ($X\Psi'(X)X_n^{-1}$) times the elasticity of the marginal benefit from the program's allocation ($-X_nB''(X_n)B'(X_n)^{-1}$).

This simple model illustrates how, for public programs with relatively large start-up costs, early capture by the non-poor could well be the only politically feasible option, particularly when those start-up costs must be financed domestically. For example, to be willing to pay taxes to cover the program's start up, the non-poor may well require a sizable share of the initial benefits, such as by assuring that the program is not located in inaccessible, and poor, areas. Only later, when marginal costs of program expansion are lower, will it be feasible politically to reach the poor. (This model also suggests a case for external financing of the start-up costs of anti-poverty programs, though this takes us beyond our present scope.)

The early capture case is illustrated in Figure 1. This is drawn as if there are equal numbers of "poor" and "non-poor". On the vertical axis we have the group-specific participation rate in the program (X_n and X_p in the above model). On the horizontal axis we have the average participation rate over both groups (X). The figure then gives the group-specific participation rate as it varies with the average rate i.e., the functions $\Psi(X)$ and $2X-\Psi(X)$ for the non-poor and poor respectively. As drawn, the non-poor capture the bulk of the gains initially, but become progressively satiated. Imagine we are currently at point A, where participation rates of the poor and non-poor are the same. From this information, the standard BIA would conclude that an expansion in the program would not benefit the poor relative to the non-poor. However, this is plainly wrong; the bulk of the gains from an aggregate expansion of the program from point A will go to the poor.

Late capture is illustrated in Figure 2. Suppose we are initially at the average participation rate B. The data on group-specific participation indicate that the poor are participating more than the non-poor. Yet the bulk of the gains from increasing the level of average participation to (say) point A are captured by the non-poor.

One expects that some public programs will be more like the early capture model in Figure 1, and others will be more like Figure 2. For example, it appears likely that better off parents will be the first to see their children gaining from public spending on schooling, but that they become satiated in due course, with marginal gains then going to the poor, as in Figure 1. By contrast, consider a food rationing scheme which is initially targeted to the poor, but in time political pressures to favor middle income groups lead to higher marginal gains to the non-poor; Figure 2 represents this case.

The above discussion suggests that the homogeneity assumptions routinely used in BIA can be deceptive for inferring how the gains and losses from public spending reforms will be distributed. The outcomes in practice will depend on the specifics of the setting. The rest of this paper will provide some evidence for India.

3. Measuring participation rates

Sampled households have been ranked by consumption expenditure (or income) per person, adjusted for differences in the cost of living. The average participation rate is the proportion of households in a given quintile (say) of consumption per person who participate in the program. The average odds-ratio of participation is given by the ratio of the quintile-specific average participation rate to the overall average. The marginal odds-ratio of participation (MOP) is defined as the increment to the program participation rate of a given quintile associated with a change in aggregate participation in that program. Differences between the marginal and average odds of participation reflect differences in the incidence of infra-marginal spending, as discussed in the last section. Only with homogeneous participation will the two be everywhere the same.

The average odds of participation can be calculated straightforwardly from the survey data. How can we estimate the MOP? We assume that only a single cross-sectional survey is available (as typically used in BIA).[9] We have data on program participation across geographic areas ("regions") within states (or it might be households within states if the micro data are

9 In some potential applications of this approach, one might have more than one cross-sectional survey available which asked about program participation. Then one could form regional panels, allowing changes over time to be studied. This would have the advantage of sweeping out any regional fixed effects, though inter-temporal measurement errors may entail a lower "signal-to-noise" ratio on the changes over time than the levels at one time.

available). We have calculated the average participation rates for a given program for each quintile and each region. The participation rate for a given quintile varies across regions according to the level of public spending on the program in the state to which each region belongs, as well as other variables (discussed further below).

To estimate the MOP by program and expenditure quintile we can regress the quintile-specific participation rates across regions on the average state participation rates (all quintiles, all regions) for each program.[10] However, Ordinary Least Squares regression will give a biased estimate of the MOP, since the region and quintile specific participation rate (on the left hand side) is implicitly included when calculating the overall mean participation rate across all regions and quintiles (on the right hand side). To deal with this problem we use an Instrumental Variables Estimator, in which the "leave-out mean" is used as the instrumental variable for the state average participation rate; the leave-out mean is defined as the mean for the state excluding the region and quintile specific participation rate corresponding to each observation in the data.[11]

How can the MOP be interpreted? As with the average participation rates, one must also know the subsidy rates for the program to infer overall incidence. In conventional BIA, the subsidy rate for each program is typically assumed to be one number, constant over income groups and geographically. (For example, it is assumed that it costs the same to the government's budget to have a poor person participate as a rich person.) Under the same assumption, the

10 Our precise method appears to be new, although models of outcome indicators stratified by socio-economic group are familiar from past work. See, for example, Deolalikar (1995) which studies the cross-sectional differences in health outcomes for poor children versus others in Indonesia.

11 So if one is using the data for quintile 3 in region 5 within state 10 then the leave-out mean is the average for all regions and quintiles within that state excluding quintile 3 in region 5.

marginal odds of participation can be used to infer the incidence by quintiles of an increase in public spending on a given program. We will be able to make partial tests of that assumption.

4. Data

Our analysis is based on India's National Sample Survey (NSS) for 1993-94. In addition to more standard data on consumption expenditures, demographics and education attainments, this round of the NSS also asked about participation in various anti-poverty programs at household level. Participation in three key programs is identified: public works schemes, a means-tested credit scheme called the "Integrated Rural Development Programme" (IRDP), and a food rationing scheme, the "Public Distribution System" (PDS). The data on participation in these programs can be collated with data on total consumption expenditure per person at the household level. Participation in public works programs is based on whether any household member worked for at least 60 days on public works during the preceding 365 days. Participation in the IRDP program is defined as whether the household received any assistance during the last 5 years from IRDP. Participation in the PDS program is defined as whether the household purchased any commodity from a ration/fair price shop during the last 30 days.

Sampled households in the NSS are ranked by total consumption expenditure (including imputed values of consumption from own production) per person normalized by state-specific poverty lines. Quintiles are defined over the entire rural population, with equal numbers of people in each. So the poorest quintile refers to the poorest 20% of the national rural population in terms of consumption per capita.

There are a number of ways in which these data are less than ideal. The relationship between IRDP participation over the last five years and consumption expenditure over the last month may well be a poor indication of the program's incidence, to the extent that participants' living standards may have changed considerably over such a period. There are also concerns about the adequacy of "participation" as an indicator of utilization for PDS; for example, the rich may only buy a small quantity of the rationed good (though this conjecture is not consistent with other data on the incidence of PDS purchases; see Radhakrishna and Subbarao, 1997). And there is the possibility that the individual participant may have a different standard of living to the household as a whole; a poor person within a non-poor household may be attracted to a public works project for example. In the case of public works, it is also likely that the question will pick up participation in public works projects which are not anti-poverty programs as such.

The sample size (rural areas only) of the 1993-94 NSS was 61,464 households. The analysis is done at the level of the NSS region, of which there are 62 in India, spanning 19 states and with each NSS region belonging to only one state. So in the basic model, for any given combination of quintile and program, we regress the sample participation rates across the 62 NSS regions on the average participation rate (irrespective of quintile) across each of the 19 states.

Recall that inferring the incidence of changes in public spending from the estimated MOP requires the common assumption in BIA that the average subsidy rate (given participation) is a constant. For Public Works Programs and IRDP there is no obvious way in which the subsidy rate conditional on participation would vary by household expenditure per person within a given state. However, variation between states can be expected. For the Public Distribution System income effects on demand for the rationed goods could well also create differences in the subsidy rate across quintiles within a given state.

We were able to test the assumption of a constant subsidy rate for Public Works Programs, IRDP and primary school enrollment. However, the data to do so were not available for the Public Distribution System. For each program, we regressed per capita spending by state on state average participation, plus four of the quintile-specific participation rates. We were unable to reject the null hypothesis that the parameter estimates on the quintile-specific participation rates were jointly zero.[12] The coefficients on the state average participation rates were highly significant, as one would expect. Thus we find no evidence that the subsidy rate varies significantly by quintile. This helps justify the standard constant-subsidy assumption of BIA when interpreting our results for these public programs.

5. Results

We begin with primary school enrollments for children aged 5-9 years. Table 1 gives the average enrollment rates from the 1993-94 NSS data.[13] Enrollment rates rise with household expenditure per capita nationally, and in all states; Table A1 in the Appendix gives the results by state. And they tend to be higher for boys than girls. However, there are marked differences between states. In Kerala there is less difference between the quintiles and between boys and

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[12] The probability values for the F-tests were, respectively, 0.57, 0.11, and 0.23 for Primary Schooling, Public Works and IRDP.

[13] Our calculated enrollment rates from the National Sample Survey are appreciably lower than those obtained from schools themselves on which official enrollment rates are based. The official primary enrollment rate for India was over 100% in 1993. There are differences in definition; for example, we have confined attention to the age group 5-9, and so missed late starters. However, though there are reasons to believe that biases in official sources lead to overestimation of enrollments in India (Kingdon, 1996).

girls (indeed, enrollment rates are slightly higher for girls from the poorest quintile in Kerala) than found in (say) Bihar or Punjab (Table A1).

It can be seen that the average enrollment rates tend to be lowest for the poorest quintile, and to increase as consumption per person increases. The average odds of enrollment suggest that subsidies to primary schooling will would mildly favor the non-poor. Notice, however, that we cannot split public from private schooling in the data, and that public school enrollments may well be lower for the well off. Figures 3 and 4 plot the enrollment rates, for the poorest and richest quintiles respectively, by region against the state averages. It can be seen that while the average enrollment rate is higher for the richer quintile, the relationship between the region-specific enrollment rates and the state average rate is steeper for the poorest quintile. Thus the MOP is higher for the poor, even though the average participation rate is lower.

Table 2 gives the estimated marginal odds of being enrolled, obtained by regressing the participation rates of each quintile across NSS regions on the state average participation rate over all programs.[14] Following the discussions above, the numbers in Table 2 can be interpreted as the gain in subsidy incidence per capita for each quintile from a one Rupee increase in aggregate spending on each program. For example, an extra 100 Rupees per capita spent on primary schools will increase the public expenditure per capita going to the poorest quintile by 110 Rupees.

The MOP estimates suggest that an expansion of primary schooling would be decidedly pro-poor at the margin. (As in standard BIA, future earnings gains from better education are not

[14] As discussed above, these are Instrumental Variables Estimates using the leave-out mean as the instrument for the state average participation rate. The lines of best fit in Figures 3 and 4 are Ordinary Least Squares.

factored into this calculation.) The implication for the incidence of subsidies to primary education is clear (given our inability to reject the constant unit subsidy assumption). While the average odds of participation in Table 1 suggest that the share of the total subsidy going to the poorest quintile is only 14% (0.71 times one fifth), the marginal odds in Table 2 imply that the poorest quintile would obtain about 22% of an increase in the total subsidy going to primary education.

There is also a gender difference between the average and marginal odds of participation by the poor. The average odds of poor kids being in school are higher for boys (0.75 versus 0.66 for girls; see Table 1). However, the marginal odds are almost identical (1.09 versus 1.08).

These results are clearly not what one would expect with homogeneous participation. Marginal gains from expanding primary schooling in rural India are much better distributed than average gains.

Turning now to the anti-poverty programs, Table 3 gives the average participation rates and average odds of participation by quintile for each of the anti-poverty programs. For both public works programs and IRDP, participation rates fall as expenditure per person increases. However, the rate of decline is not large; the odds of the poorest quintile participating in public works programs is 1.23, versus 0.83 for the richest quintile; the rate of decline is even lower for IRDP. Participation rates amongst the richest 20% in terms of consumption per person are high even for public works programs. For PDS, the participation rate is actually lowest for the poorest quintile, with highest participation amongst the middle expenditure quintile.

These are national aggregates. The Appendix (Table A2) gives a breakdown of the participation rates by state. We find large differences between states. In Orissa, the proportion of households in the poorest quintile participating in public works programs is over four times higher than for the richest quintile; the odds of the poorest 20% participating is 1.6, well above the national mean (Table 3). For Maharashtra, the odds of the poorest quintile participating in public works programs is also well above the national average. At the other extreme, one finds states such as Andhra Pradesh, Gujarat, Kerala, and Tamil Nadu where the poorest quintile have a below average participation rate.

Table 4 gives the estimated marginal odds of participation. (The regional plots for all programs and the poorest and richest quintiles, analogous to Figures 3 and 4 for schooling, are available from the authors.) The MOP for the poorest quintile is highest for public works programs, while IRDP dominates for the three middle quintiles; the PDS has the highest MOP for the richest quintile. The MOP coefficients broadly confirm the conclusion from the average odds of participation (Table 3) that the public works programs perform best at reaching the poorest, while IRDP is more effective in reaching the middle quintiles, including those living at India's poverty line (at roughly the 40th percentile).

The difference between the MOP numbers for any two programs gives the estimated gain from switching one Rupee between the two programs. For example, switching 100 Rupees per capita from PDS to public works programs would increase public spending per capita on the poorest quintile by 10 Rupees (116-106=10, using the basic model).

For both the public works programs and IRDP, it is notable that the marginal odds of participation tend to fall more steeply as one moves from the poorest to the richest quintiles than do the average odds (Table 3). Thus the average odds underestimate how "pro-poor" an increase in average spending on each of these programs will be. This is particularly strong for IRDP, for which the average odds of participation are only slightly higher for the poorest quintile than the richest (1.03 versus 0.89), while there is a large difference in the MOP (1.11 versus 0.39). When compared to the average odds of participation (as normally used in benefit incidence studies), the share of the total IRDP spending imputed to the poorest 40% of the population is 11% higher, while that imputed to the richest 20% is 56% lower. For PDS, however, there is less difference between the average and marginal odds, so the former are a better guide to PDS incidence than for the other two programs.

As with primary school enrollments, these results are inconsistent with the homogeneity assumptions routinely made in benefit incidence analysis. We do not see the same reversal between average and marginal odds as we did in Tables 1 and 2; for the anti-poverty programs, both average and marginal odds of participation tend to be higher for the poor. However, as with schooling, marginal gains from these programs tend to be better distributed than average gains, as indicated by the fact that the marginal odds tend to be relatively lower for the non-poor than the average odds.

Before concluding, it is worth reviewing some of the assumptions which underpin our efforts to estimate the marginal incidence of spending on these programs. As described in section 3, we estimated the MOP by regressing quintile-specific participation rates across regions on the average participation rates (all quintiles, all regions) for each program. No other explanatory variables (such as state-level poverty rates) were included in this specification. To the extent that such variables matter to quintile-specific participation via their influence on state average participation rates, they are not of concern, since it is the effect of expansion in the overall size of the program which we are interested in evaluating. There is, however, one way in which our simple specification may be unsatisfactory. Section 2 outlined how political economy factors could influence program incidence. Yet, by not including political economy variables as separate explanatory variables in our regression, we implicitly assume that those elements of the political economy configuration which determine the timing of program capture are identical across states.

While we were unable to control for regional fixed-effects in our estimations since we do not have time series data, we were able to probe the above assumption to some extent. First, we re-ran each model by regressing quintile and region-specific participation rates on a full set of state dummy variables, for each program. We then compared the R^2's from these regressions to those that had obtained from our regressions on state participation rates. We found that in most cases the R^2's from the state-level participation rate specifications were above 70% of those from the state fixed-effect regression, indicating that our state average participation rate variable was able to capture nearly as much of the variation in the dependent variable as a specification which allowed each state to exercise a separate impact.[15]

Second, we examined the residuals from our regression utilizing state average participation rates, to see whether for any given state and quintile, the average of the residuals across regions was significantly higher or lower than that observed for other states. For example, are the participation rates amongst the bottom quintile in Kerala or West Bengal (both of which have had long periods of left-wing governments) unusually high given the state average participation rate, reflecting a difference in the political-economy, favoring the poor? We found

[15] In the case of primary schooling of boys, the R^2's from our specification declined from about 75% of the R^2 from the state fixed-effect specification for the lowest two quintiles to an average of about 45% for the top two quintiles. In the case of Public Works programs, the ratio of R^2's averaged around 50% for the three lowest quintiles, and rising to 70% for the 4th, and then declining to 31% for the top quintile.

no regular patterns in these average state-level residuals. In very few cases (looking at the average residuals per state, for each of the quintile-specific and program-specific regressions) did the average residual per state exceed in absolute value the standard error of the regression as a whole. And in the few cases where this did occur, there was no discernible pattern in which a given state appeared to be consistently more effective in reaching a particular quintile across programs. The only pattern which does emerge is that for primary school enrollment in both Haryana and Punjab (of boys, girls, and jointly), the average residuals for the bottom quintile were uniformly negative and larger than one standard error. On dropping these two states (on the presumption that the political economy is appreciably different), our estimate of the marginal incidence of additional spending on education in the poorest quintile were slightly higher than in Table 2; for boys the MOP rose to 1.16, for girls it was 1.12, and the average was 1.13.[16] So the direction of changes adds support to our main result on the comparisons of the average and marginal odds of participation.

6. Conclusions

"Benefit incidence" analyses are often used to infer the distributional impact of changes in public outlays on a social program, based on average participation rates conditional on income or some other welfare metric. The inferences drawn for public spending reform could be wrong if program participation is nonhomogeneous, such that the composition of participants varies with the size of the program.

[16] For the second poorest quintile the MOP was 0.98 for boys, 0.99 for girls, and 1.01 overall.

Motivated by a simple model of the political-economy of program capture, we have used Indian data to test the homogeneity assumption of benefit incidence methodology. We have offered a relatively simple method of estimating the marginal odds of program participation. The method uses inter-regional differences in program scale to infer how the composition of participation varies with program expansion or contraction. The method can be implemented with the same basic data used by conventional benefit-incidence analysis.

We find that the average participation rates are not a reliable guide to the distributional impacts of small changes in aggregate public outlays or reallocations between programs. Our estimates of the marginal odds of participation based on the inter-regional variation broadly confirm the qualitative conclusion from the average participation numbers for the three poverty programs we have studied here. However, we find that the average odds of participation — as are typically used in benefit incidence calculations — greatly understate how pro-poor extra spending on either public works programs or the means-tested credit scheme is likely to be, and (conversely) conventional methods underestimate the loss to the poor from program cuts. The average odds also underestimate how pro-poor a switch from (say) the food distribution system to public works programs will be in India.

In the case of primary schooling, the average odds of participation also give the wrong qualitative result on whether expansion is pro-poor. While the average odds of enrollment rise with expenditure per person, the marginal odds fall sharply indicating that expansion is decidedly pro-poor. Indeed, the marginal odds suggest that current subsidies to primary education are about as pro-poor as the best of the programs directed (explicitly) at fighting poverty.

For both primary schooling and the poverty programs (except the food rationing scheme), our results are more consistent with the "early capture" model described by Figure 1 than by the "late capture" model of Figure 2. The geographic pattern of participation by quintile suggests that the non-poor tend to be the first to gain when a program is introduced, but that high marginal gains to the poor emerge later.

References

Besley Timothy, and Ravi Kanbur, 1993, "Principles of Targeting", in Michael Lipton and Jacques van der Gaag (eds) *Including the Poor*, Washington DC: World Bank.

Bidani, Benu, and Martin Ravallion, 1997, "Decomposing Social Indicators using Distributional Data", *Journal of Econometrics*, 77: 125-140.

Demery, Lionel, 1997, "Benefit Incidence Analysis", mimeo, World Bank, Washington DC.

Deolalikar, Anil B., 1995, "Government Health Spending in Indonesia: Impacts on Children in Different Economic Groups", in D. van de Walle and K. Nead (eds) *Public Expenditures and the Poor*, Baltimore: Johns Hopkins University Press.

Gelbach, Jonah and Lant Pritchett, 1997, "Redistribution in a Political Economy: Leakier Can be Better", mimeo, World Bank, Washington DC.

Hammer, Jeffrey S., Ijaz Nabi, and James A. Cercone, 1995, "Distributional Effects of Social Sector Expenditures in Malaysia, 1974-89", in D. van de Walle and K. Nead (eds) *Public Expenditures and the Poor*, Baltimore: Johns Hopkins University Press.

Kingdon, Geeta G., 1996, "Private Schooling in India: Size, Nature and Equity Effects", Working Paper 72, Development Economics Research Programme, London School of Economics.

Lipton, Michael and Martin Ravallion, 1995, "Poverty and Policy", in Jere Behrman and T.N. Srinivasan (eds) *Handbook of Development Economics Volume 3* Amsterdam: North-Holland.

Medel, Braulio, Agustin Molína, and José Sánchez, 1992, "Distributional Effects of Public Expenditures in Spain, 1981", *Public Finance* 47: 271-286.

Meesook, Oey A., 1984, "Financing and Equity in the Social Sectors in Indonesia", World Bank Staff Working Paper 703, World Bank, Washington DC.

Piggott, John and John Whalley, 1987, "Interpreting Net Fiscal Incidence Calculations", *Review of Economics and Statistics* 69: 685-94.

Radhakrishna, R., and K. Subbarao, 1997, "India's Public Distribution System: A National and International Perspective," World Bank Discussion Paper 380, World Bank, Washington DC.

Selden, Thomas M., and Michael J. Wasylenko, 1992, "Benefit Incidence Analysis in Developing Countries", Policy Research Working Paper 1015, World Bank, Washington DC.

van de Walle, Dominique, 1995, "The Distribution of Subsidies through Public Health Services in Indonesia, 1978-87", in D. van de Walle and K. Nead (eds) *Public Expenditures and the Poor*, Baltimore: Johns Hopkins University Press.

____________________, 1998, "Assessing the Welfare Impacts of Public Spending", *World Development* 26(3): 365-79.

Table 1: Average primary school enrollment in rural India

Quintile	Boys		Girls		Total	
	Enrollment rate (%)	Average odds of enrollment (mean=1.0)	Enrollment rate (%)	Average odds of enrollment (mean=1.0)	Enrollment rate (%)	Average odds of enrollment (mean=1.0)
Poorest	42.6	0.75	31.6	0.66	37.2	0.71
2nd	53.4	0.93	43.1	0.91	48.6	0.90
3rd	60.5	1.07	50.3	1.06	55.8	1.08
4th	66.1	1.16	58.6	1.26	62.6	1.21
5th	69.9	1.23	65.2	1.38	67.7	1.31

Note: The table gives the average primary school enrollment rates as a percentage of children aged 5-9, and the odds of enrollment, defined as the ratio of the quintile-specific enrollment rate to the mean rate. Calculations based on the 1993-94 National Sample Survey.

Table 2: Marginal odds of primary school enrollment

Quintile	Boys	Girls	Total
Poorest	1.09	1.08	1.10
	(6.90)	(9.65)	(8.99)
2nd	0.91	0.91	0.97
	(6.05)	(6.99)	(7.92)
3rd	0.92	0.84	0.87
	(5.85)	(6.54)	(7.65)
4th	0.66	0.66	0.67
	(4.10)	(4.28)	(4.77)
5th	0.53	0.70	0.67
	(4.08)	(5.53)	(5.69)

Notes: The table gives the instrumental variables estimate of the regression coefficient of the quintile-specific primary school enrollment rates across regions on the average rate by state for that program, based on the 1993-94 National Sample Survey. The leave-out mean state enrollment rate is the instrument for the actual mean. The numbers in parentheses are t-ratios.

Table 3: Average participation rates for India's main anti-poverty programs in rural areas

Quintile of expenditure per capita	Public Works Programs		Integrated Rural Development Program		Public Distribution System	
	Participation rate (%)	Average odds of participation (mean=1.0)	Participation rate (%)	Average odds of participation (mean=1.0)	Participation rate (%)	Average odds of participation (mean=1.0)
Poorest	5.0	1.23	6.5	1.03	69.5	0.92
2nd	4.6	1.13	7.1	1.13	76.7	1.01
3rd	4.2	1.04	6.4	1.03	77.9	1.03
4th	3.5	0.86	6.0	0.96	78.1	1.00
5th	3.4	0.83	5.6	0.89	76.1	1.00

Note: The table gives the average participation rates and the odds of participation, defined as the ratio of the quintile-specific participation rate to the mean participation rate for each program. Calculations based on the 1993-94 National Sample Survey.

Table 4: Marginal odds of participation for India's anti-poverty programs

Quintile	Public Works Programs	Integrated Rural Development Program	Public Distribution System
Poorest	1.16	1.11	1.06
	(3.27)	(15.49)	(8.14)
2nd	0.93	1.28	0.99
	(3.64)	(17.73)	(7.26)
3rd	0.80	1.21	0.91
	(2.98)	(23.52)	(6.88)
4th	0.92	0.96	0.86
	(4.32)	(19.09)	(7.16)
5th	0.55	0.39	0.81
	(3.29)	(8.06)	(6.27)

Notes: The table gives the instrumental variables estimate of the regression coefficient of the quintile-specific program participation rates across regions on the average participation rate by state for that program, based on the 1993-94 National Sample Survey. The leave-out mean state participation rate is the instrument for the actual mean. The numbers in parentheses are t-ratios.

Appendix: Participation Rates by State, Rural India, 1993-94

Table A1: Primary School Enrollment for Children Aged 5-9

State	Quintile	Boys	Girls	All
ANDHRA PRADESH	bottom	38.4	30.6	34.3
	2nd	46.6	40.7	43.3
	3rd	55.1	39.4	47.2
	4th	64.0	48.9	56.2
	top	61.4	61.1	61.3
	TOTAL	56.2	46.9	51.4
ASSAM	bottom	52.0	50.1	51.2
	2nd	64.1	59.7	62.0
	3rd	65.2	66.6	65.9
	4th	76.4	72.4	74.5
	top	83.4	78.1	81.1
	TOTAL	63.7	61.4	62.7
BIHAR	bottom	36.6	19.8	28.7
	2nd	47.0	36.8	42.6
	3rd	58.5	45.3	53.3
	4th	59.7	54.4	57.6
	top	75.6	61.3	68.6
	TOTAL	47.5	33.4	41.2
GOA	bottom	n.a	n.a	n.a.
	2nd	n.a	n.a	n.a
	3rd	67.9	67.6	67.7
	4th	66.6	71.2	69.3
	top	80.3	88.6	85.4
	TOTAL	76.5	74.2	75.1
GUJARAT	bottom	51.1	43.2	46.9
	2nd	60.0	43.0	52.1
	3rd	67.2	57.8	62.5
	4th	67.4	66.9	67.2
	top	64.6	67.6	65.8
	TOTAL	63.6	56.7	60.4
HARYANA	bottom	34.7	21.8	28.1
	2nd	46.0	47.7	46.9
	3rd	60.5	35.9	49.0
	4th	66.3	59.8	62.7
	top	77.9	63.8	71.6
	TOTAL	59.3	47.3	53.3

State	Quintile	Boys	Girls	All
HIMACHAL PRADESH	bottom	70.1	55.4	60.9
	2nd	76.0	73.8	74.8
	3rd	82.5	80.9	81.6
	4th	88.8	86.8	87.9
	top	90.4	89.3	89.9
	TOTAL	82.5	76.7	79.5
KARNATAKA	bottom	43.8	28.0	36.3
	2nd	64.6	57.7	61.0
	3rd	61.2	63.0	62.1
	4th	74.2	62.6	68.3
	top	77.4	71.6	74.7
	TOTAL	63.7	55.9	59.9
KERALA	bottom	75.4	79.0	77.0
	2nd	88.6	83.8	86.4
	3rd	88.3	85.9	87.2
	4th	84.6	78.2	81.8
	top	79.3	90.0	85.0
	TOTAL	83.5	84.1	83.8
MADHYA PRADESH	bottom	35.8	28.2	31.9
	2nd	48.9	33.9	41.9
	3rd	51.0	43.1	47.3
	4th	63.1	62.2	62.7
	top	64.7	55.4	60.6
	TOTAL	50.1	41.1	45.8
MAHARASHTRA	bottom	55.1	46.5	50.5
	2nd	64.1	59.3	61.8
	3rd	71.5	66.0	68.9
	4th	73.6	72.3	73.0
	top	80.6	69.8	75.6
	TOTAL	66.8	59.3	63.2
ORISSA	bottom	35.2	27.3	31.3
	2nd	50.9	39.5	45.4
	3rd	54.5	51.7	53.2
	4th	57.2	46.2	51.4
	top	65.9	57.1	61.6
	TOTAL	47.5	39.2	43.4

State	Quintile	Boys	Girls	All
PUNJAB	bottom	37.7	22.7	29.2
	2nd	63.5	51.3	58.0
	3rd	76.2	57.9	67.2
	4th	81.1	76.3	79.2
	top	80.1	87.0	83.0
	TOTAL	74.9	66.6	71.2
RAJASTHAN	bottom	40.3	14.4	27.3
	2nd	49.3	20.6	34.9
	3rd	49.5	26.4	39.1
	4th	59.7	29.0	45.8
	top	64.1	51.4	58.3
	TOTAL	53.5	28.4	41.7
TAMIL NADU	bottom	66.7	66.5	66.6
	2nd	75.0	69.0	72.3
	3rd	77.2	71.3	74.2
	4th	81.8	82.1	82.0
	top	76.7	91.5	83.9
	TOTAL	75.0	74.2	74.6
UTTAR PRADESH	bottom	42.4	24.5	34.3
	2nd	47.4	32.1	40.9
	3rd	57.9	42.7	51.0
	4th	55.9	46.8	52.0
	top	63.7	54.0	59.1
	TOTAL	51.3	37.1	45.0
WEST BENGAL	bottom	36.6	36.4	36.5
	2nd	48.7	44.8	46.9
	3rd	59.8	50.4	55.4
	4th	69.5	72.9	71.1
	top	80.0	76.1	77.9
	TOTAL	53.3	49.9	51.7
DADRA & NAGAR	bottom	62.3	44.9	55.5
	2nd	65.8	66.7	66.2
	3rd	100.0	40.1	65.3
	4th	97.4	29.3	51.0
	top	83.5	100.0	86.0
	TOTAL	70.2	50.9	62.3
DELHI	bottom	n.a.	n.a.	n.a.
	2nd	n.a.	n.a.	n.a.
	3rd	41.7	36.8	38.7
	4th	100.0	100.0	100.0
	top	66.5	68.7	62.7
	TOTAL	70.0	57.6	65.0
NATIONAL	TOTAL	56.6	47.0	52.1

Table A2: Participation Rates by State for Three Anti-Poverty Programs

State	Quintile	% participating in Public Works Programs	% participating in the IRDP Program	% with access to the Public Distribution System
ANDHRA PRADESH	poorest	2.3	2.5	79.0
	2nd	2.7	2.9	87.0
	3rd	4.1	4.3	84.5
	4th	3.3	4.4	82.5
	5th	3.2	4.0	81.8
	TOTAL	3.3	4.0	82.8
ASSAM	poorest	3.6	4.3	84.3
	2nd	3.6	2.8	86.4
	3rd	4.9	2.2	87.6
	4th	2.0	1.9	86.5
	5th	1.7	2.9	84.7
	TOTAL	3.4	2.7	86.2
BIHAR	poorest	5.4	5.8	68.7
	2nd	5.8	6.0	77.6
	3rd	4.4	5.0	76.2
	4th	2.8	4.6	78.1
	5th	3.9	2.9	75.2
	TOTAL	4.8	5.2	74.4
GOA	poorest	0.0	0.0	65.1
	2nd	0.0	0.0	100.0
	3rd	0.0	0.0	100.0
	4th	4.6	0.0	100.0
	5th	2.3	2.7	92.1
	TOTAL	2.3	1.8	93.8
GUJARAT	poorest	2.6	11.3	84.2
	2nd	4.6	11.6	90.2
	3rd	3.9	8.6	88.5
	4th	2.3	9.9	86.3
	5th	2.4	7.4	83.8
	TOTAL	3.0	9.1	86.3
HARYANA	poorest	2.5	7.3	86.9
	2nd	5.1	6.8	93.2
	3rd	2.0	7.3	91.2
	4th	2.1	9.5	90.0
	5th	2.1	6.0	86.3
	TOTAL	2.6	7.2	89.0

State	Quintile	% participating in Public Works Programs	% participating in the IRDP Program	% with access to the Public Distribution System
HIMACHAL PRADESH	poorest	8.4	5.4	88.0
	2nd	8.2	8.5	89.8
	3rd	9.0	5.6	91.3
	4th	5.9	4.9	91.1
	5th	3.0	4.3	82.8
	TOTAL	6.2	5.5	88.0
KARNATAKA	poorest	2.9	2.8	75.5
	2nd	4.0	6.8	78.4
	3rd	2.5	5.5	78.9
	4th	2.4	5.1	76.5
	5th	3.0	5.8	78.1
	TOTAL	2.9	5.4	77.6
KERALA	poorest	1.5	3.4	93.4
	2nd	2.9	5.6	96.3
	3rd	3.5	5.2	94.3
	4th	4.2	4.2	94.5
	5th	3.7	4.1	89.4
	TOTAL	3.5	4.4	92.8
MADHYA PRADESH	poorest	5.8	9.7	60.7
	2nd	5.7	11.5	66.3
	3rd	4.9	6.8	67.8
	4th	5.2	8.3	70.6
	5th	5.7	9.6	72.1
	TOTAL	5.5	9.2	67.5
MAHARASHTRA	poorest	9.7	7.7	58.8
	2nd	8.0	9.6	68.1
	3rd	8.4	8.4	73.3
	4th	6.5	8.6	77.3
	5th	4.1	5.1	73.3
	TOTAL	7.1	7.7	70.5
ORISSA	poorest	9.4	6.2	72.6
	2nd	5.7	5.6	77.9
	3rd	5.9	5.3	83.6
	4th	3.3	7.2	87.3
	5th	2.2	6.3	81.7
	TOTAL	5.9	6.1	79.8

State	Quintile	% participating in Public Works Program	% participating in the IRDP Program	% with access to the Public Distribution System
PUNJAB	poorest	0.0	4.7	67.3
	2nd	3.9	0.5	66.9
	3rd	2.3	6.1	65.7
	4th	2.3	2.2	71.4
	5th	1.9	4.4	72.8
	TOTAL	2.1	3.8	70.5
RAJASTHAN	poorest	4.2	5.7	62.9
	2nd	6.5	7.1	57.9
	3rd	4.8	5.3	64.0
	4th	4.3	4.0	57.6
	5th	2.6	5.5	53.6
	TOTAL	4.2	5.4	58.1
TAMIL NADU	poorest	2.0	7.5	87.5
	2nd	1.9	5.1	86.2
	3rd	3.0	6.2	89.7
	4th	2.4	5.3	87.2
	5th	4.3	5.5	83.6
	TOTAL	2.9	5.8	86.6
UTTAR PRADESH	poorest	4.0	6.4	55.9
	2nd	4.1	7.0	63.2
	3rd	4.2	8.1	62.6
	4th	3.6	6.7	63.5
	5th	2.9	6.7	63.7
	TOTAL	3.8	7.0	61.6
WEST BENGAL	poorest	3.6	6.2	90.2
	2nd	2.4	8.3	91.9
	3rd	1.8	8.2	90.7
	4th	2.4	5.8	90.0
	5th	3.0	5.8	88.6
	TOTAL	2.6	7.0	90.4
DADRA & NAGAR	poorest	3.4	67.0	69.8
	2nd	1.7	77.8	73.1
	3rd	5.9	75.0	68.6
	4th	1.0	58.0	71.9
	5th	0.0	25.4	72.1
	TOTAL	2.3	60.7	71.3
DELHI	poorest	-	-	-
	2nd	0.0	0.0	100.0
	3rd	0.0	0.0	48.3
	4th	3.3	0.0	100.0
	5th	1.7	0.0	53.0
	TOTAL	1.6	0.0	55.5
NATIONAL	TOTAL	4.1	6.3	75.8

Figure 1: Early Capture

Participation is no higher for the poor at point A, but they capture the bulk of the gains from program expansion

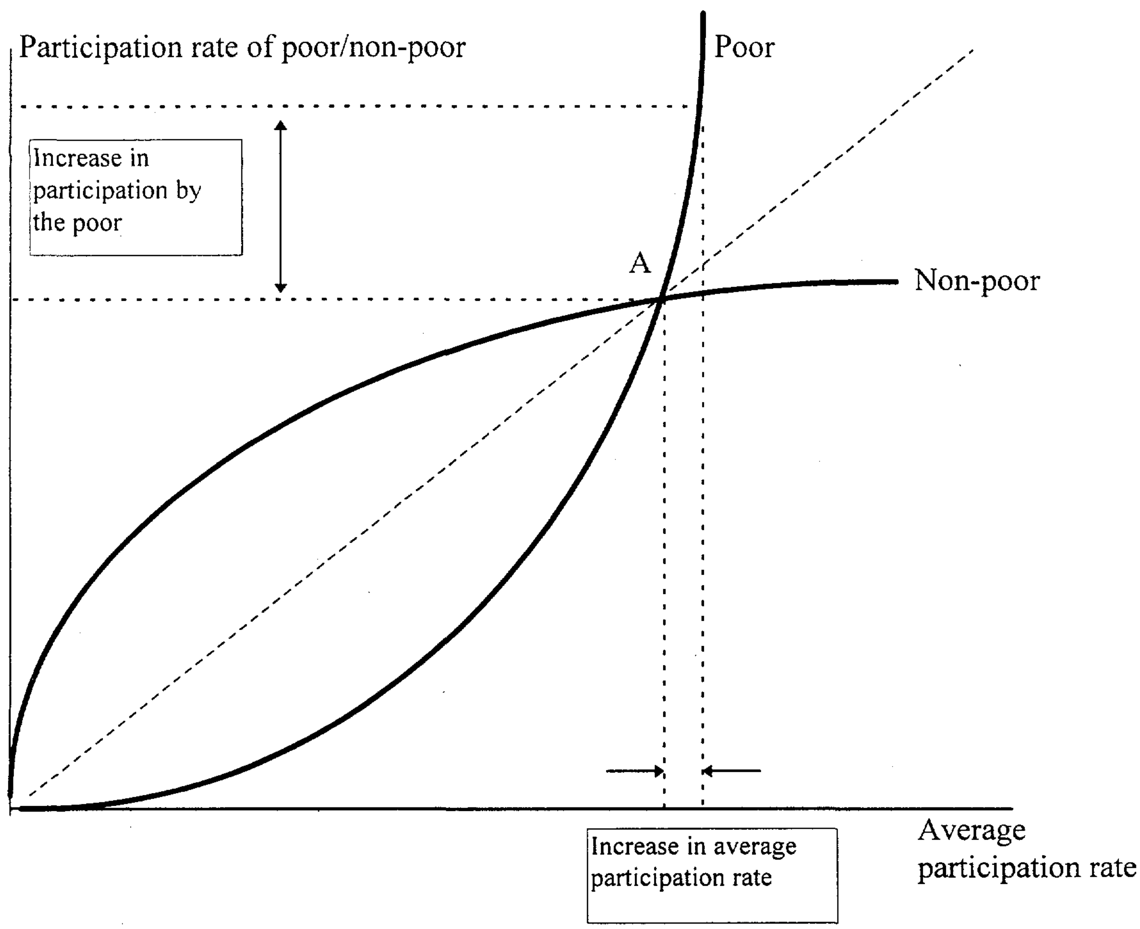

Figure 2: Late Capture

Participation is higher for the poor at point B, but expansion favors the non-poor

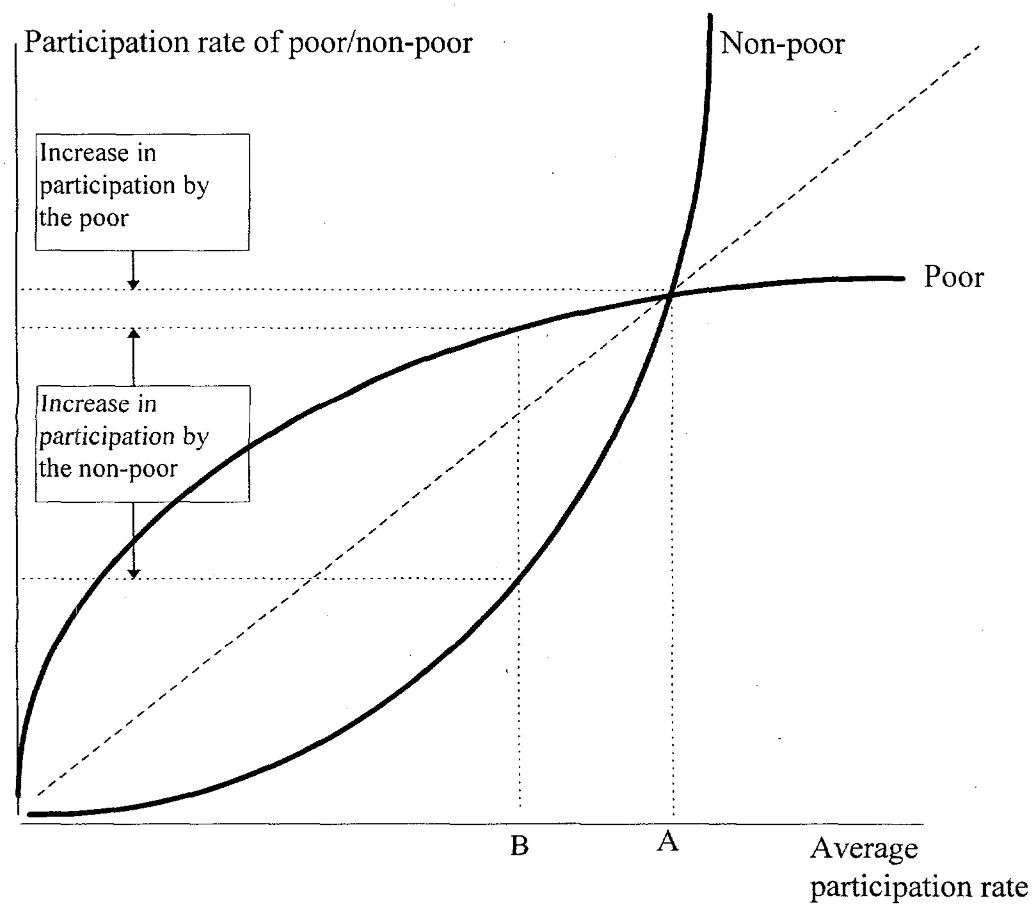

Figure 3

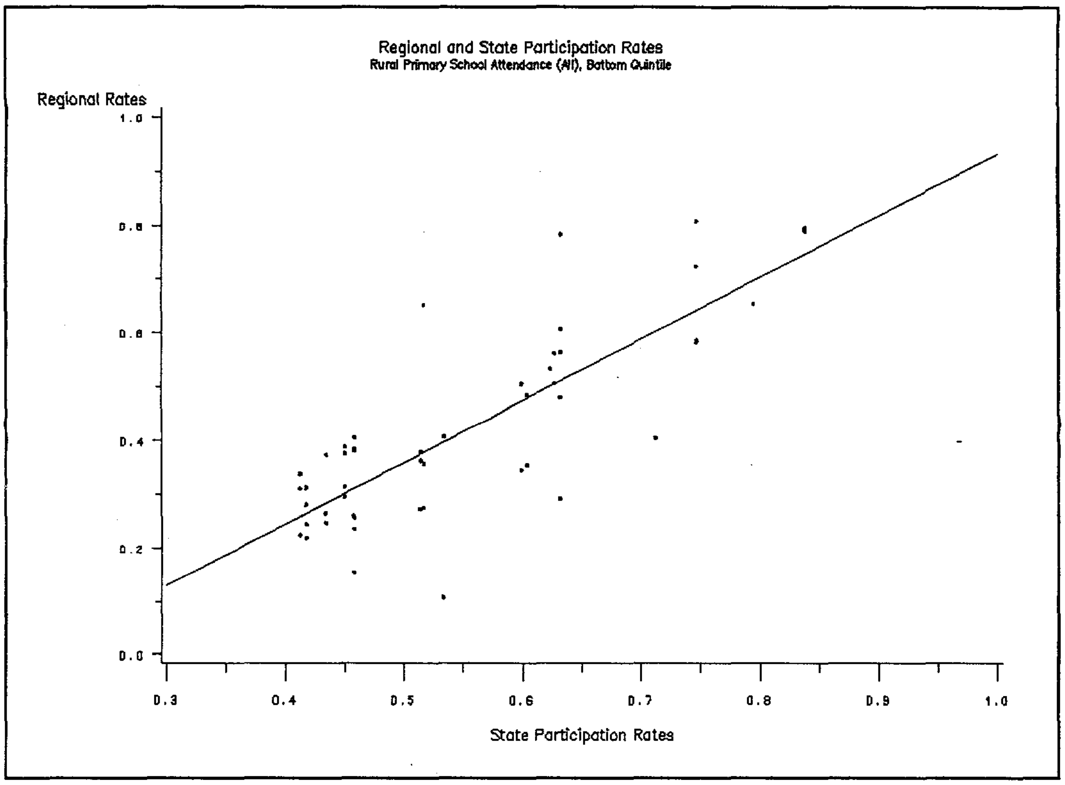

Figure 4

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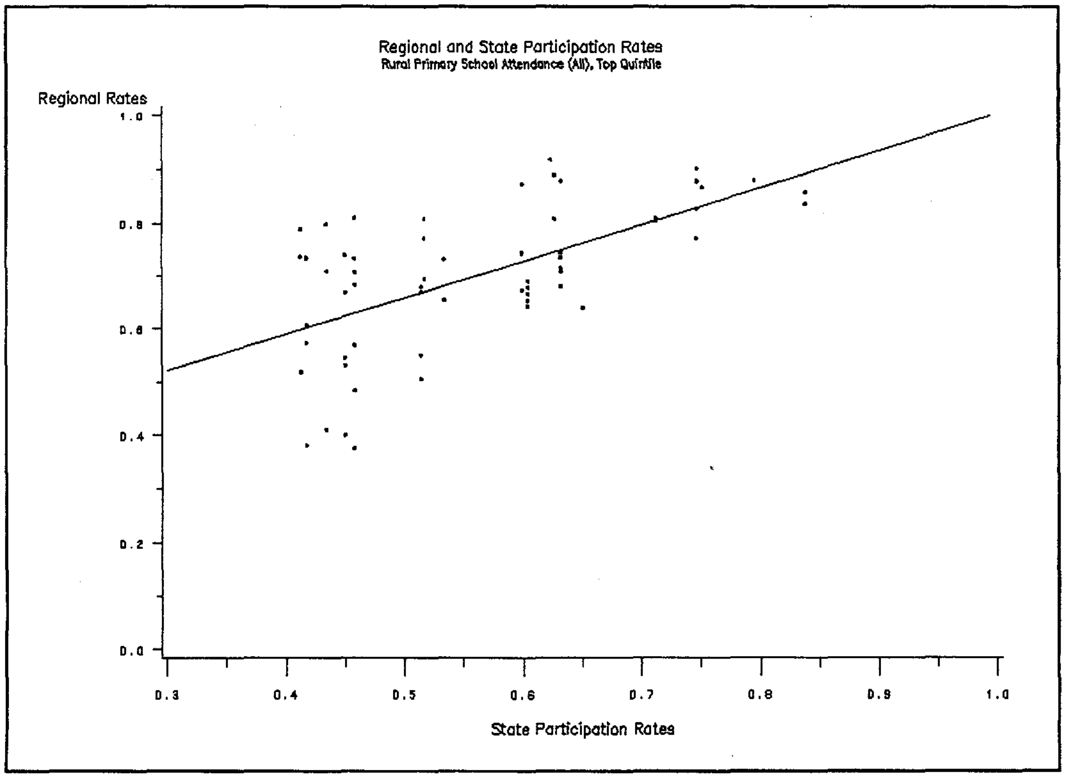

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